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Exploring the impact of intelligent learning tools on students' independent learning abilities: a PLS-SEM analysis of grade 6 students in China

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The purpose of this study was to investigate the influence of interaction quality and information quality of intelligent learning tools on students' satisfaction and intention to use these tools, as well as to examine the relationship between the intention to use intelligent learning tools and students' independent learning abilities. The study utilized Smart-PLS 3, a Partial Least Squares Structural Equation Modeling (PLS-SEM), to analyze data collected from 384 Grade 6 students in China. The results of the study showed that (a) intention to use intelligent learning tools had a significant and direct impact on students' independent learning abilities; (b) interaction quality did not have a significant impact on intention to use, but information quality and satisfaction with the tools did have an impact on intention to use; (c) interaction quality and information quality indirectly influenced intention to use through students' satisfaction with the tools. Furthermore, this research provided valuable recommendations for improving the interaction quality and information quality of intelligent learning tools, which can ultimately enhance students' independent learning abilities.

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Introduction

The development of intelligent technology has brought great changes to the way of learning. Intelligent learning tools have emerged as indispensable aides, bolstering students' blended learning, collaborative learning, and adaptive learning experiences (Osadcha et al., 2021). Refer to Merayo et al. (2018), intelligent learning tools are learning places or activity spaces that can provide convenient learning support for students. These tools possessed the ability to automatically capture and discern learners' personality characteristics, tailoring personalized learning resources accordingly. Moreover, they facilitated automated assessment of the learning process and could be seamlessly accessed across diverse terminal devices in a multimodal fashion.

Intelligent learning tools were based on a multitude of emerging technologies, including big data, artificial intelligence, and learning analytics (Wang et al., 2019). These tools offered a diverse range of functionalities, such as intelligent essay assessment, visual feedback on evaluation outcomes, human-machine interaction, and personalized resource recommendations. By leveraging these intelligent learning tools, students gained access to customized personalized materials, automated assignment evaluation, dynamic interactive experiences, and adaptive responses (Chen et al., 2021).

With the increasing prevalence of mobile devices and advancements in information technology, the number of intelligent learning tools has increased in online learning environments (Herrador-Alcaide et al., 2020). The exploration of how to effectively leverage intelligent learning tools to enhance student learning has garnered extensive attention. Several studies have examined the design, development, and utilization of intelligent learning tools, leveraging technologies such as artificial intelligence, big data, virtual reality (VR), and voice recognition to support collaborative, personalized, and adaptive learning (Faqih and Jaradat, 2021; Fu et al., 2020; Parsola et al., 2019).

In order to make better use of diverse online resources, students needed to possess digital proficiency and great self-directed learning abilities (Zhu and Bonk, 2022). Independent learning ability plays a crucial role while using the intelligent learning tools. Many researchers have investigated the influence of intelligent learning tools on independent learning ability, revealing their positive impact on developing students' independent learning abilities (Beckers et al. (2019); Jeong, 2022). Moreover, numerous researchers have explored various factors that influence the use of intelligent learning tools, aiming to optimize their classroom integration. Factors such as self-efficacy, prior experience, satisfaction, and infrastructure have been identified as potential determinants of tool utilization (Al-Qaysi et al., 2023; Botero-Gomez et al., 2022; Valencia-Arias et al. (2018)). Additionally, some researchers have investigated the impact of intelligent learning tool usage on students' development of soft skills (Deep et al., 2019). However, there is a lack of research that elucidates the impact of interaction quality and information quality of intelligent learning tools on students' independent learning abilities.

Based on the above research statements, few studies have explored how intelligent learning tools affect students' learning. This study aims to explore the information of interaction quality and information quality of intelligent learning tools on students' satisfaction, intention to use, and independent learning abilities. The ultimate goal is to provide recommendations for optimizing intelligent learning tools to enhance students' independent learning abilities. The research questions are as follows:

1. Whether interaction quality and information quality of intelligent learning tools have impacts on students' satisfaction and intention to use the intelligent learning tools?
2. Whether intention to use the intelligent learning tools has an impact on students' independent learning abilities?

As the next section, "Literature review and hypotheses" provides a literature review and develops hypotheses. The method is described in "Methodology", while the statistical analyses and results are elaborated in "Results". Based on the above results, "Discussion" section makes a discussion. Finally, a conclusion of this study, along with limitations and future research are drawn in "Conclusion, limitation and future research".

Literature review and hypotheses

Interaction quality. Intelligent learning tools provide students with an online interactive and collaborative learning space. The primary interaction methods for intelligent learning tools include synchronous interactions (video, audio, live chat rooms) and asynchronous interactions (email, discussion boards). This study divided interaction quality into three categories based on the features of intelligent learning tools and Moore's (1989) research: learner-learner interactions, learner-instructor interactions, and learner-content interactions. Numerous studies have demonstrated that the quality of interaction was a critical factor in determining students' levels of satisfaction (Gasell et al. (2022), but the results of the three interactions were different (Çakiroğlu and Kahyar, 2022). Kuo et al. (2014), Gray and DiLoreto (2016), Alqurashi (2019) argued learner-content and learner-instructor interaction strongly predicted satisfaction, and learner-learner interaction weakly predicted satisfaction. However, Moore (2014), Rautela et al. (2022) and Atamturk (2023) found learner-learner interactions had the greatest impact on students' satisfaction. A meta-analysis by Bernard et al. (2009) found interaction quality could increase the intention to use. Therefore, this study suspected the interactive quality of intelligent learning tools had impacts on satisfaction and intention to use. We hypothesize that:

H1. The interaction quality of intelligent learning tools has positive influence on satisfaction with tools.

H2. The interaction quality of intelligent learning tools has positive influence on intention to use.

Information quality. As part of the DeLone and McLean model (D&M) of information systems success, information quality was often used to measure system quality (DeLone and McLean, 2003). Information quality refers to the information provided by the system that was exactly what you need (Saba, 2012). Accuracy, timeliness, completeness, relevance, readability, consistency were the main characteristics which determined the quality of systems information (DeLone and McLean, 2003; Gable et al., 2008). In this study, information quality refers to the quality of the information that the intelligent learning tools provided, including accuracy, understandability, relevance, and abundant resources. Accuracy entails that the information provided is free of errors and completely accurate. Understandability is a key metric, indicating that the information should be easy for users to comprehend (Muda and Erlina, 2019). Relevance denotes that the information provided should be directly pertinent to users' needs, avoiding digressions and including all necessary details (Shahzad et al., 2021). Abundant resources refer to a comprehensive range of materials, that are abundant in both quality and quantity, which can be videos and texts (Sabeh et al., 2021).

Many studies have explored the relationships among information quality, satisfaction, and intention to use empirically. Hassanzadeh et al. (2012) and Efiloğlu (2019) tested the relationship between information quality and satisfaction, and found the association was significant. High quality information created a positive experience, which contributed to the enhancement of satisfaction (Liu et al., 2021). A study measured factors that influenced students' use of intelligent learning tools during the Covid-19 pandemic, and found that the low-quality of information was the biggest obstacle to students' intention to use tools (Maatuk et al., 2022). On the contrary, Zhang et al. (2022) collected data via questionnaires and system logs, and reported that information quality did not have a significant positive impact on behavioral intention. Literature studies showed that the information quality had a positive impact on user satisfaction, but the impacts on user intention were controversial, which was worth exploring. Therefore, we hypothesize that:

H3. The information quality of intelligent learning tools has positive influence on the satisfaction with tools.

H4. The information quality of intelligent learning tools has positive influence on intention to use.

Satisfaction with tools. Satisfaction is the important link between learning tools and usage in multiple models, such as the expectation confirmation model (ECM) (Bhattacherjee, 2001) and D&M (DeLone and McLean, 2003). In this study, satisfaction with intelligent learning tools refers to the user's contentment with their tool experience. Research has shown that the level of satisfaction with tools was not only related to users' intention to use (Nikou and Economides, 2017; Park and Kim, 2014), but also to their intention to continue using the tools (Hsiao et al., 2016; Saeed et al. (2020)). Students' intention to use was affected by their attitude toward the platform or system (Masa'deh et al., 2022; Song and Kong, 2017). Mailizar et al. (2021) examined the factors influencing intention to use and identified satisfaction as one of the most prominent factors. It was evident that students' satisfaction was a critical determinant of learning outcomes (Pérez-Pérez et al., 2020). Based on this, our study argued that students' satisfaction with tools was a crucial factor that influences their intention to use these tools. We hypothesize that:

H5. Students' satisfaction with intelligent learning tools has positive influence on intention to use.

Intention to use. As an attitude, intention plays a critical role in the use of intelligent learning tools, influencing students learning. Intention was defined as the likelihood that people used the systems (Mohammadi, 2015). Davis and Venkatesh (1996) stated that the intention to use was the degree to which users intended to use or increased their use. In this study, intention to use refers to the extent to which students are willing to use intelligent learning tools. It's found that intention to use was reported in technology acceptance model (TAM), unified theory of acceptance and use of technology (UTAUT) and D&M models, pointing to individual impact (Mardiana et al., 2015). The relationship between intention and behavior was controversial (Sheeran and Webb, 2016). Fife-Schaw et al., (2007) argued that the change of intention did not guarantee the change of behavior, the result was mainly influenced by abstainers. DeLone and McLean (2003) found that higher satisfaction with information systems was expected to increase intention to use, leading to positive impacts on individuals. Students who possessed independent learning abilities could actively seek out information and take effective measures to deal with tasks (Zimmerman, 2013). Therefore, it is necessary to improve students' independent learning abilities. With regards to intention, previous research has primarily investigated potential factors influencing students' intention to use, such as perceived usefulness and perceived ease of use (Al-Rahmi et al., 2019; Park, 2009). However, less research has explored the relationship between intention to use and independent learning abilities, which is worth investigating. Thus, this study attempted to explore the effects of intention to use on independent learning abilities. We hypothesize that:

H6. Students' intention to use intelligent learning tools has positive influence on independent learning abilities.

Independent learning ability. Independent learning ability has a profound impact on our society of learners (Hockings et al., 2018). Independent learning emphasized the resources and environment in which learners learned independently, and the school or institution that provided these resources was called open learning center or self-access center (Broady and Kenning, 1996; Thomas et al., 2015). In this approach, learners were responsible for setting their own goals, selecting materials, and evaluating learning activities, rather than relying on the teacher (Benson, 2013; Brookfield, 1986; Holec, 1979). Autonomy and control were critical elements of self-regulated learning, which required learners to monitor the effectiveness of their learning methods and strategies on their own (Paris and Paris, 2003; Zimmerman, 1990). During online learning, students were required to learn independently without the direct support of teachers or other students (Scheel et al. (2022)). This aligns with the characteristics of independent learning that are promoted by intelligent learning tools. Independent learning through these tools was an active, self-regulated, and constructive process that required a high degree of autonomy (Bransford et al. (2000); Tavangarian, 2004). However, Hockings et al. (2018) found that some students still relied heavily on teachers' guidance during online learning, which limited the full potential of independent learning. On one hand, independent learning abilities during online learning increased students' motivation and self-confidence, leading to higher academic achievements (Davies et al., 2013; Heckman and Annabi, 2005). On the other hand, students with higher independent learning abilities were better equipped to utilize intelligent learning tools effectively, and the use of these tools also promoted the development of students' independent learning abilities (Kingsbury, 2014; Macaskill and Taylor, 2010; Zhao et al., 2014). Therefore, it is important to explore which factors of intelligent learning tools affect or promote students' independent learning abilities.

Research model. Based on the above hypotheses, the research model has been developed in Fig. 1. We hypothesized that intelligent learning tools' interaction quality and information quality had a positive influence on students' intention to use intelligent learning tools, which could eventually affect students' independent learning abilities.

Methodology

Participants. This study used convenience sampling method to distribute a questionnaire on the usage of intelligent learning

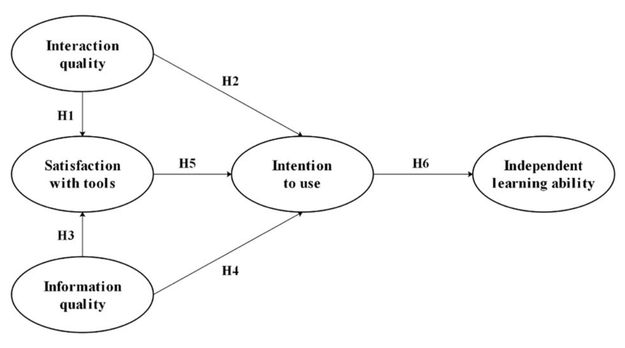

Fig. 1 The research model of the impact of the intelligent learning tools on students' independent learning abilities.

tools to students at a public primary school in grades 6 in Hangzhou, Zhejiang Province, China. The sixth grade is a critical period for students' development of independent learning abilities, which also provides them with increased opportunities to utilize intelligent learning tools for their studies. An online questionnaire platform Wenjuanxing (https://www.wjx.cn/) was utilized to collect data in 2022. This questionnaire informed participants of their rights, the purpose of the study, and the degree of confidentiality of personal information prior to distribution so that participation in the study was entirely voluntary. A total of 384 valid questionnaires were compiled. All of the participants remaining have used intelligent learning tools previously. Detailed demographic information about the participants is listed in Table 1. Overall, most of the respondents maintained the habit of using intelligent learning tools several times a week, which was affected by boarding in schools.

Table 1 Demographic profile of respondent.

Demographic profile		Frequency	Percentage
Academic level	Top 30%	161	41.93%
	Middle 40%	194	50.52%
	Last 30%	29	7.55%
Years of using the Internet	Less than 5 years	217	56.51%
	5–10 years	144	37.50%
	More than 10 years	23	5.99%
Frequency of use intelligent learning tools	Not commonly used	82	21.35%
	Several times a month	71	18.49%
	Several times a week	172	44.79%
	Every day	59	15.36%

Instrument development. We used a questionnaire with two parts to test the research model. The first part is about the participants' demographic profile, including academic performance, years of using the Internet and frequency of using the intelligent learning tools. The second part consisted of five subscale, 19 items: information quality (4 items), interaction quality (4 items), independent learning ability (4 items), satisfaction with tools (3 items) and intention to use (4 items). Each item was measured using a five-point Likert scale, with answer choices ranging from "disagree strongly" (1) to "agree strongly" (5), and most of these items were adapted from the extant literature. Table 2 shows the scale and references.

Data analysis. The statistical data analysis was performed using Smart-PLS 3. Partial Least Squares Structural Equation Modelling (PLS-SEM) supported by Smart-PLS 3 was performed to estimate the effects among the hypothesis constructs. PLS-SEM is now widely applied in many social science disciplines (Hair et al., 2012), which emphasizes prediction in estimating statistical models (Sarstedt et al. (2021); Wold, 1982), and allows researchers to estimate complex models without imposing distributional assumptions on the data. With 384 data, five potential variables and 19 observed variables in this study, the model becomes more complex. Given such outcome, PLS-SEM is suitable for this study.

A PLS-SEM approach is performed to test the research model via two-step data analysis: measurement model and structural model. In the first step, the measurement model is assessed in

Table 2 Sources of indicators.

Constructs	Indicators	Sources
Information quality (IFQ)	IFQ1-The knowledge presented in the intelligent learning tools I have used is error-free. IFQ2-The learning content in the intelligent learning tools I have used is easy to comprehend. IFQ3-The learning content in the intelligent learning tools I have used meets my needs. IFQ4-The intelligent learning tools I have used provide a wide range of learning resources.	DeLone and McLean (2003)
Interaction quality (ITQ)	ITQ1-The intelligent learning tools I use provide me with regular learning reports. ITQ2-The intelligent learning tools I use recommend suitable learning resources to me. ITQ3-I am able to interact with teachers when using intelligent learning tools. ITQ4-I am able to interact with classmates when using intelligent learning tools.	Pituch and Lee (2006) Wang and Chiu (2011) Zhao and Lu (2012)
Independent learning ability (ILA)	ILA1-By using intelligent learning tools, I am able to develop my learning plans more effectively. ILA2-The use of intelligent learning tools has enabled me to better manage my study time. ILA3-Intelligent learning tools have allowed me to adapt my learning methods to the content I am studying. ILA4-Intelligent learning tools have helped me to be more reflective about what I have learned.	Zimmerman (1990)
Satisfaction with tools (ST)	ST1-I am satisfied with using intelligent learning tools. ST2-My learning needs can be fulfilled by using intelligent learning tools. ST3-I prefer to use intelligent learning tools rather than offline learning.	Bhattacherjee (2001) Wang and Liao (2008)
Intention to use (IU)	IU1-I am willing to use intelligent learning tools actively for my learning. IU2-I am willing to keep using intelligent learning tools for my learning. IU3-I am willing to increase the frequency of my usage of intelligent learning tools. IU4-I am willing to recommend exceptional intelligent learning tools to others.	Roca et al. (2006) Lee (2010)

IFQ information quality, *ITQ* interaction quality, *ILA* independent learning ability, *ST* satisfaction with tools, *IU* intention to use.

regard to reliability and validity. Once the measurement model adequacy is established, the second step is the assessment of the structural model for its capacity to predict.

Results

Common method bias. Before formally analyzing the data, the Harman's single-factor test was conducted using SPSS 26 to examine the issue of common method bias. The largest factor accounted for 46.127% of the variance, which was below the threshold of 50%, indicating that there was no significant problem of common method bias in this study's data.

Assessment of the model fit. To verify the model fit, we calculated the values of SRMR, d_ULS, d_G, Chi-Square and NFI using the PLS algorithm in Smart PLS 3 (See Table 3). The results indicated that SRMR < 0.08, d_ULS < 0.95, d_G < 0.95, NFI > 0.9, which align with the fit criteria proposed by Henseler et al. (2016), indicating a good model fit.

Measurement model evaluation. The measurement model, as the first stage in PLS-SEM approach, was assessed by determining the reliability and validity of the measures (Ooi and Tan, 2016) and endorsing their reliability, convergent validity and discriminant validity. The results of the measurement model assessment were shown in Table 4.

The indicators' reliability is evaluated by Cronbach's alpha and composite reliability, which should exceed the thresholds of 0.70 and 0.60 respectively. In the study, Cronbach's alpha values for all the constructs were above 0.810, which indicates a good level of reliability. The values of composite reliability (CR) ranged from 0.888 to 0.953, which was higher than the recommended cut-off value of 0.70 (Hair et al., 2021). Moreover, the Dijkstra-Henseler indicator (rho_A) has a minimum value of 0.840, exceeding the critical value of 0.7. Consequently, the reliability criteria were met both at item and construct levels (Hair et al., 2019).

The validity of the measurements is assessed through convergent and discriminant validity. Convergent validity is achieved when the outer loading of each indicator is above 0.7 and the average variance extracted (AVE) of each construct is 0.5 or above (Henseler et al., 2015). Table 4 shows that all of the loadings are above 0.7 and AVE values exceeded 0.5 demonstrating the convergent reliability of the constructs.

If the value of the square root of AVE is higher than the absolute value of the correlation coefficient between pairs of constructs (Chin, 1998) and the indicators are all highly loaded on their own respective constructs (Wong et al., 2016), it means that there is good discriminant validity. It is shown that the square root of all construct AVE values in this study are higher than the correlation coefficients among the constructs (Table 5).

Henseler et al. (2015) proposed the Heterotrait-Monotrait Ratio (HTMT) to measure the discriminant validity in PLS-SEM. HTMT represents the estimate for the construct's correlation with the other constructs, that should be smaller than one (Henseler et al., 2016). The results of HTMT assessment in Table 6 ranged between 0.672 and 0.804, indicating the discriminant validity of the constructs.

Structural model evaluation. As the appropriateness of the measurement model has been established, the structural model should be examined, to provide evidence for the proposed theoretical relationships. Standard assessment criteria, which should be considered, include the coefficient of determination (R^2), the blindfolding-based cross-validated redundancy measure (Q^2), as well as the statistical significance and relevance of the path coefficients (Hair et al., 2019). Before evaluating the structural model, collinearity must be examined to ensure that regression results are not affected. Variance inflation factor (VIF) values are used to detect collinearity problems. VIF values lower than 5 are indicative of no collinearity issues among the predictor constructs, the lower the VIF value, the better (Hair et al., 2017). The

Table 3 Model fit.

Fit Summary	Saturated model
SRMR	0.066
d_ULS	0.825
d_G	0.345
Chi-Square	797.537
NFI	0.902

Table 4 Summary results for the reflective outer model.

Constructs	Indicators	Loadings	Cronbach's alpha	Rho_A	Composite reliability (CR)	Average variance extracted (AVE)
ITQ	ITQ1	0.874	0.854	0.874	0.900	0.694
	ITQ2	0.866				
	ITQ3	0.796				
	ITQ4	0.792				
ST	ST1	0.905	0.810	0.850	0.888	0.728
	ST2	0.924				
	ST3	0.715				
IU	IU1	0.896	0.834	0.840	0.890	0.670
	IU2	0.841				
	IU3	0.770				
	IU4	0.761				
IFQ	IFQ1	0.742	0.861	0.880	0.905	0.706
	IFQ2	0.870				
	IFQ3	0.891				
	IFQ4	0.851				
ILA	ILA1	0.939	0.933	0.934	0.953	0.834
	ILA2	0.919				
	ILA3	0.927				
	ILA4	0.867				

IFQ information quality, *ITQ* interaction quality, *ILA* independent learning ability, *ST* satisfaction with tools, *IU* intention to use.

Table 5 The discriminant validity.

	ILA	IFQ	IU	ITQ	ST
ILA	**0.913*** **				
IFQ	0.612	**0.841*** **			
IU	0.727	0.598	**0.819*** **		
ITQ	0.700	0.620	0.628	**0.833*** **	
ST	0.736	0.604	0.784	0.694	**0.853*** **

IFQ information quality, *ITQ* interaction quality, *ILA* independent learning ability, *ST* satisfaction with tools, *IU* intention to use.
***$p < 0.001$ (in bold).

Table 6 The discriminant validity.

	ILA	IFQ	IU	ITQ	ST
ILA					
IFQ	**0.672*** **				
IU	0.825	**0.698*** **			
ITQ	0.777	0.705	**0.727*** **		
ST	0.831	0.691	0.947	**0.804*** **	

IFQ information quality, *ITQ* interaction quality, *ILA* independent learning ability, *ST* satisfaction with tools, *IU* intention to use.
***$p < 0.001$ (in bold).

Table 7 Inner VIF values.

	ILA	IFQ	IU	ITQ	ST
ILA					
IFQ			1.793		1.624
IU	1.000				
ITQ			2.199		1.624
ST			2.130		

IFQ information quality, *ITQ* interaction quality, *ILA* independent learning ability, STsatisfaction with tools, IU intention to use.

Table 8 Result of structural model examination.

Hypotheses	Paths	Path coefficients	*T*-values	Remarks
H1	ITQ → ST	0.519***	9.451	Supported
H2	ITQ → IU	0.097^{NS}	1.550	Unsupported
H3	IFQ → ST	0.282***	5.107	Supported
H4	IFQ → IU	0.165***	3.705	Supported
H5	ST → IU	0.617***	12.497	Supported
H6	IU → ILA	0.727***	25.051	Supported

IFQ information quality, *ITQ* interaction quality, *ILA* independent learning ability, *ST* satisfaction with tools, *IU* intention to use.
***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, $^{NS}p > 0.05$.

inner VIF values of this study are between 1.000 and 2.199 (Table 7), indicating collinearity issues do not affect the structural model.

In this study, 5000 samples were repeatedly sampled by bootstrapping to verify the relationship between the variables of the model. As shown in Table 8 and Fig. 2, all the path coefficients of the inner model are statistically significant ($p <$ 0.001), except hypothesis 2.

The interpretation of variation (R^2) refers to the predictive power of the independent variable to predict the dependent variable in a model (Memon et al., 2017), which can assess a

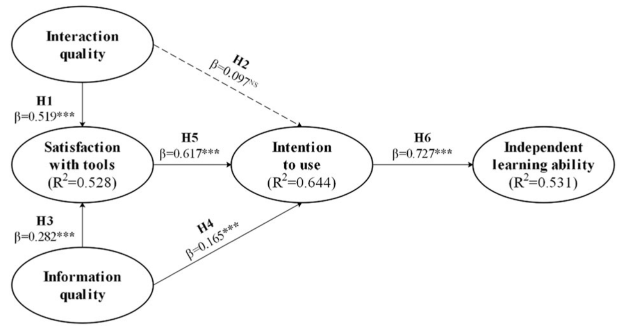

Fig. 2 The structural model of the impact of the intelligent learning tools on students' independent learning abilities.

Table 9 Predictive accuracy and predictive relevance.

Endogenous constructs	R^2	Q^2
ST	0.531	0.376
IU	0.644	0.426
ILA	0.528	0.436

ILA independent learning ability, *ST* satisfaction with tools, *IU* intention to use.

model's predictive accuracy through the coefficient of determination (Hair et al., 2014).

In general, R^2 values of 0.75, 0.50, and 0.25 can be interpreted as being substantial, moderate, and weak (Hair et al., 2019; Henseler et al., 2009). The higher the variance explained, the higher the predictive accuracy a structural model has on its endogenous constructs. From the results of the structural model test in Tables 7 and 8, interaction quality ($\beta = 0.519$, $p < 0.001$) and information quality ($\beta = 0.282$, $p < 0.001$) have a significant positive impact on satisfaction with tools ($R^2 = 0.528$), explained 52.8% of the variance. Satisfaction with tools ($\beta = 0.617$, $p < 0.001$) and information quality ($\beta = 0.165$, $p < 0.001$) have a significant positive impact on intention to use ($R^2 = 0.644$), explained 64.4% of the variance. It's surprising to find that satisfaction with tools ($\beta = 0.617$, $p < 0.001$) alone could explain 61.7% of the variance in intention to use ($R^2 = 0644$). Intention to use ($\beta = 0.727$, $p < 0.001$) has a significant positive impact on independent learning ability ($R^2 = 0.531$), explained 53.1% of the variance. However, interaction quality ($\beta = 0.097$, $p < 0.05$) has no significant direct influence over intention to use ($R^2 = 0.644$). Generally, all the hypotheses were supported except hypothesis 2.

Q^2 is another metric for evaluating the prediction accuracy of Partial Least Squares (PLS) path models based on the blindfolding procedure. As a rule of thumb, Q^2 values higher than 0, 0.25, and 0.5 depict small, medium, and large predictive relevance of the PLS path model (Hair et al., 2019). As shown in Table 9, the minimum Q^2 value is 0.376, higher than the standard of 0.25, indicating that the model has good predictability.

Inspecting the mediating effects. Given that the insignificant direct role of interaction quality on intention to use might be possibly attributed to the mediating effects exerted by satisfaction with tools, we further conducted a post-hoc mediation analysis using the Bootstrap method. Followed the approach advocated by Nitzl et al. (2016) and Hair et al. (2021), full mediation happens when the direct effect is insignificant, while partial mediation takes place if the direct effect is significant. From Table 10, it is evidenced that satisfaction with tools could fully mediate the influence of interaction quality on intention to use. The indirect

Table 10 Mediation test.

Paths	Indirect effects	*T*-values	Direct effects	*T*-values	Remarks
ITQ → ST → IU	0.320***	7.232	0.097^{NS}	1.550	Full mediation
IFQ → ST → IU	0.174***	4.792	0.165***	3.705	Complementary partial mediation

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***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, $^{NS}p > 0.05$.

effect of interaction quality on intention to use was weighted at 0.320. Additionally, satisfaction with tools is also playing a partial mediating role between information quality and intention to use. The indirect effect of information quality on intention to use was weighted at 0.174.

Discussion

The influence of intention to use intelligent learning tools on students' independent learning abilities. The results showed that students' intention to use the intelligent learning tools directly predicted independent learning ability (H6). The mean score for students' independent learning abilities ($M = 3.82$) was high in this study. These results aligned with previous surveys conducted by Radha et al. (2020) and Prasetyanto et al. (2022), which demonstrated that the use of intelligent learning tools improved students' independent learning abilities. One possible explanation was that students' intention to use intelligent learning tools increased the frequency of tool usage, prompting students to use these tools in their learning. The cultivation of independent learning abilities couldn't be achieved overnight, but students' willingness to use intelligent learning tools could facilitate their continuous use, which created conditions for the development of independent learning abilities. Independent learning was one of the most used strategies in online learning. When students were willing to utilize intelligent learning tools, they were more inclined to embrace the assistance provided by these tools in their subject learning. For instance, students showed a willingness to utilize the adaptive and ubiquitous resource platform, BiliBili, to access learning materials. Students who displayed ambitious intentions for tool usage typically exhibited greater independent learning abilities. However, students scored low in increasing the frequency of using intelligent learning products ($M = 3.40$), which negatively impacted the development of their independent learning abilities. When students were willing to use intelligent learning tools, they became more proactive in finding learning resources and developing study plans. In summary, the degree of students' intention to use intelligent learning tools played a crucial role in fostering their independent learning abilities.

The influence of intelligent learning tools' interaction quality and information quality on students' intention to use intelligent learning tools. The results suggested that information quality and satisfaction with intelligent learning tools had a significant direct impact on intention to use (H4 and H5). The information quality of intelligent learning tools has been unanimously recognized by students ($M = 4.01$). Moreover, students exhibited strong usage intentions ($M = 3.80$), which aligned with previous research studies (Albaom et al., 2022; Nicolaou and McKnight, 2006; Osatuyi et al., 2022). Information quality captured the advantages of using intelligent learning tools, while satisfaction reflected the level of recognition and acceptance of these tools. It was noteworthy that satisfaction with the tools exerted a greater influence on users' intention to use them. The utilization of big data analysis and personalized recommendations ensured that the information provided by intelligent learning tools was tailored to meet the specific needs of students. This was particularly important for personalized learning tools such as Homework Help. Thus, based on the above hypotheses, we inferred that the more accurate and comprehensible the information provided and the richer the available resources, the higher the level of student satisfaction. As a result, this satisfaction further strengthened the willingness to use intelligent learning tools.

However, this study found that the interaction quality of intelligent learning tools had no significant impact on intention to use (H2). This finding was consistent with the research conducted by Dai et al. (2020) and Alzahrani et al. (2022), who also reported that the interaction quality had the least impact on students' willingness to use online tools. This study confirmed that the average score for information quality ($M = 4.02$) of intelligent learning tools was higher than that of interaction quality ($M = 3.88$). One possible explanation for this result was that current intelligent learning tools primarily focus on knowledge dissemination through learning activities such as watching micro-lectures, reading learning materials, completing practice exercises, and reviewing problem-solving processes. Therefore, the information quality of intelligent learning tools, such as course content and learning resources, better meet the needs of students, while the importance of interaction quality was often overlooked, as it did not directly stimulate students' intention to use the tools. It was observed that the mediating effect of satisfaction with the tools may potentially explain the insignificant relationship. Interactions with classmates, teachers, and the learning system did not directly stimulate students' willingness to use intelligent learning tools. Instead, this intention was achieved by enhancing students' satisfaction with the tools. Although interaction quality was important for students' satisfaction with intelligent learning tools, its impact on usage intention might be limited when the purpose of interaction was to help students overcome feelings of distance and enhance their sense of presence.

Satisfaction with intelligent learning tools as a mediator. More importantly, satisfaction with intelligent learning tools was found associated with interaction quality and information quality (H1 and H3), which was a mediator influencing the intention to use intelligent learning tools. Hamann et al. (2012) discovered that students' satisfaction with tools was influenced by the quality of interaction, particularly the interactions between students and teachers. Students who preferred face-to-face learning expressed concerns about the lack of full support from teachers in the online learning process (Akcil and Bastas, 2020; Bessette, 2020). Intelligent learning tools could address this issue by offering features such as multiplayer video and voice calls, screen sharing, file transfer, and more. As a result, students could effectively communicate with their peers and teachers, leading to higher satisfaction with intelligent learning tools, which was particularly prominent in primary schools. Additionally, interactive features that provided timely and visual feedback were identified as crucial, as they offered students immediate response and sensory information. In this study, DingTalk was the most frequently utilized intelligent learning tool by students due to its capacity for real-time interaction.

As illustrated by Cidral et al. (2018), information quality was one of the decisive factors in students' satisfaction. This was reasonable because the essence of any intelligent learning tool was to provide students with understandable, relevant, accurate, and resourceful information that was related to their learning. When the information catered to students' needs, enabling them to access suitable learning resources when necessary, their satisfaction with the tool increases. This finding aligned with the research conducted by Hammouri and Abu-Shanab (2018), where higher levels of satisfaction were observed when the information provided was accurate and comprehensive. Information quality represented the knowledge quality of intelligent learning tools. In comparison to other age groups, elementary school students exhibited underdeveloped metacognitive abilities, hence making accurate information more imperative for them. The results indicated that when students perceived the tool as user-friendly for interaction and capable of delivering high-quality information, their satisfaction levels were more likely to escalate.

Practical implications. This study delved into the impact of intelligent learning tools on students' independent learning abilities, yielding valuable practical implications for designers and developers of such tools. The findings underscored the significance of interaction quality and information quality in shaping students' satisfaction with and intention to use these tools, ultimately influencing their independent learning abilities. Designers and developers, therefore, need to give particular attention to these factors as they greatly influence students' positive behavioral intentions towards intelligent learning tools. First of all, designers and developers should prioritize the development of a user-friendly communication interface and offer diverse interaction methods. Regarding learner-instructor interactions, timely feedback and guidance from teachers could encourage students to be more engaged in their studies. When it comes to learner-instructor interactions, providing timely feedback and guidance from teachers can stimulate students' active involvement in their studies. Facilitating learner-learner interactions, such as through discussion boards and exchange rooms, fosters a sense of community among students. As for learner-content interactions, regular learning reports and personalized resource recommendations can provide students with a comprehensive overview of their learning progress, enabling them to adapt their study plans accordingly. By incorporating these strategies, designers and developers can enhance the usability and effectiveness of intelligent learning tools in supporting students' independent learning journey.

Secondly, equal attention should be given to the information quality of intelligent learning tools. Ensuring the accuracy and comprehensibility of the learning content provided by these tools is crucial, as it directly influences students' satisfaction and intention to use them. When the learning content aligns with students' needs and the information is easily accessible when required, they are more inclined to prefer using these tools. Furthermore, the availability of abundant resources offers students more options and enables them to study effectively. Developers can leverage big data technology to recommend suitable learning resources to users. Therefore, the development of interaction quality and information quality in intelligent learning tools is paramount to enhancing students' satisfaction and intention to use them, ultimately leading to the improvement of students' independent learning abilities.

Conclusion, limitation and future research

Based on the questionnaire of 384 Grade 6 students from China, this study examined how the interaction quality and information quality of intelligent learning tools impacted students' independent learning abilities. The results showed that interaction quality and information quality had direct impacts on satisfaction, and strongly affected the intention to use through satisfaction. Furthermore, intention to use was found to be a strong predictor of independent learning abilities. Information quality had a direct effect on intention to use, whereas interaction quality did not. The study aimed to provide recommendations for improving intelligent learning tools to enhance students' learning efficiency by examining the relationship between interaction quality, information quality, satisfaction, intention to use, and independent learning abilities.

However, there are some limitations in this study which require further research. Firstly, the samples were only from one school, so the scope was limited and may not be representative of a larger population. Secondly, while the study explored the impact of interaction quality, it did not specify the type of interaction being measured. Different types of interaction may have different impacts on students' satisfaction and intention to use. Future research could comprehensively analyze the use of intelligent learning tools from multiple perspectives, such as the influence of teachers and parents. Additionally, future research should focus on how to effectively guide and direct students in using intelligent learning tools to improve their independent learning abilities.

Data availability

All data generated or analyzed during this study are included in this published article and its supplementary file.

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Author contributions
The authors confirm their contribution to the paper as follows: study conception and design: RP, JY, LL, HY; data collection: RP, LZ, ZQ; analysis and interpretation of results: RP, JY; original draft preparation: RP, ZQ, LZ; language service: RP, ZQ. All authors reviewed the results and approved the final version of the manuscript.

Competing interests
The authors declare no competing interests.

Ethical approval
The author sought and gained ethical approval from Research Ethics Committee of the Jing Hengyi School of Education at Hangzhou Normal University (No. 2022028) on June 20, 2022. All procedures in this study were in accordance with the institutional research and the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Informed consent
Informed consent was obtained from all the participants.

Additional information
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